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LCI METHODOLOGY AND DATABASES

Temporal differentiation of background systems in LCA: relevance of adding temporal information in LCI databases

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Abstract
Purpose Because the potential impacts of emissions and extractions can be sensitive to timing, the temporal aggregation of life cycle inventory (LCI) data has often been cited as a limitation in life cycle assessment (LCA). Until now, examples of temporal emission and extraction distributions were restricted to the foreground processes of product systems. The objective of this paper is to evaluate the relevance of considering the temporal distribution of the background system inventory.
Methods The paper focuses on the global warming impact category for which so-called dynamic characterization factors (CFs) were developed and uses the ecoinvent v2.2 database as both an example database to which temporal information can be added and a source of product systems to test the relevance of adding temporal information to the background system. Temporal information was added to the elementary and intermediate exchanges of 22 % of the unit processes in the database. Using the enhanced structure path analysis (ESPA) method to generate temporally differentiated LCIs in conjunction with time-dependent global warming characterization factors, potential impacts were calculated for all 4,034 product systems in the ecoinvent database.
Results and discussion Each time, the results were calculated for (1) systems in which temporal information was only added to the first two tiers, representing studies in which only the foreground system is temporally differentiated, and (2) systems in which temporal information was also added to the background system. For 8.6 % of the database product systems, adding temporal differentiation to background unit processes affected the global warming impact scores by more than 10 %. For most of the affected product systems, considering temporal information in the background unit processes decreased the global warming impact scores. The sectors that show most sensitivity to the temporal differentiation of background unit processes are associated with wood and biofuel sectors.
Conclusions Even though the addition of temporal information to unit processes in LCI databases would not benefit every LCA study, the enhancement can be relevant. It allows for a more accurate global warming impact assessment, especially for LCAs in which products of biomass are present in substantial amounts. Relevance for other impact categories could be discussed in further work.

Keywords Dynamic LCA · Global warming · LCI databases · Temporal differentiation · Time

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1 Introduction

Life cycle assessment (LCA) results make it possible to compare the environmental performances of products or services, supporting decision-making by consumers, industries and governments. The level of sophistication of an LCA model should reflect the robustness required to support a particular decision-making context (Bare et al. 1999).

A possible enhancement of interest is the inclusion of temporal information in LCA. Traditionally in LCA, emissions are aggregated over time, hence assuming that all emissions and extractions occur at a single point in time. However, it was shown that impacts can be sensitive to the timing of the

emissions and extractions in a product life cycle. The lack of dynamic representations or historical data has often been cited as an important limitation of LCA (Reap et al. 2008).

In order for LCA to effectively include temporal aspects, three elements are required: temporally differentiated characterization factors (CFs), a method to combine temporal information to generate temporally differentiated life cycle inventories (LCIs) and temporal information on the unit process level. They are discussed below.

1.1 Temporally differentiated CFs

There are two aspects of extraction and emission timing that are relevant in impact assessment. First, the moment of the day or the season when the emissions occur is critical to certain impact categories. Seasonal variations are important in some contexts when assessing photochemical smog (Shah and Ries 2009), aquatic eutrophication (Hauschild et al. 2002), water availability (UNEP 2011) or human toxicity (Manneh et al. 2012), while diurnal variations are associated with ozone formation (Hauschild et al. 2002) and the human health impact of noise (Cucurachi et al. 2012). Annual variations in the background concentrations of environmental pollutants are also significant when considering the acidification impact category (Potting et al. 1998).

Second, timing is relevant when an impact assessment is carried out over a finite and fixed time horizon (e.g. 100-year time horizon for global warming). Indeed, in these situations, to remain consistent with the selected time horizon, the emissions occurring earlier should cause more potential impact than those occurring towards the end of the time period. The issue is more significant for long-life products and processes, impacts assessed over a relatively short period of time and impact categories with a large variation in environmental persistency between substances, such as global warming (Levasseur et al. 2010), metal toxicity (Huijbregts et al. 2001) and ozone depletion (Guo and Murphy 2012). While impact categories other than global warming are usually evaluated for hypothetical infinite time horizons (Hauschild et al. 2002), accounting for alternative (shorter) time periods in a sensitivity analysis for every impact category is considered best practice (European Commission 2011).

Since emissions are usually aggregated to a single point in time, the information required to consistently handle fixed and finite time horizons is missing (Levasseur et al. 2011). Methods to overcome this limitation were proposed, mainly for the global warming impact category. Among them (Kendall and Price 2012; O'Hare et al. 2009; Kendall et al. 2009) are approaches that address distortion related to emission timing for specific contexts of study. Levasseur et al. (2010) proposed the *dynamic LCA method*, which is applicable to several impact categories for non-specific context and can be used to calculate and apply time-dependent CFs to any gap between the moment of emission and the selected time horizon (see more information in Electronic Supplementary Material). While chiefly applied for the global warming impact category (Levasseur et al. 2010, 2012a, b), the method was recently used to develop time-dependent CFs to assess the aquatic ecotoxicity impacts of metals (Lebailly et al. 2013).

1.2 Calculating temporally differentiated LCIs

Temporally differentiated LCIs are required to use time-dependent CFs. The typical LCA algorithm to generate LCIs is as follows (Suh and Heijungs 2007):

$$g = \mathbf{E}\left((\mathbf{I}-\mathbf{B})^{-1}f\right) \tag{1}$$

where $\boldsymbol{E}$ is the $m \times n$ intervention matrix describing m exchanges in the environment of n unit processes of the system; $\boldsymbol{B}$ corresponds to (**I-A**) where $\boldsymbol{A}$ is the $n \times n$ technological matrix describing supplier exchanges; f is the $n \times 1$ final vector describing the system output and g is the $m \times 1$ vector corresponding to the system inventory.

However, the matrix inversion solution flattens LCI information, limiting temporal differentiation to the foreground system.

Another approach to solving the system of linear equations is power series expansion (Bourgault et al. 2012; Suh and Heijungs 2007; Peters 2007). This approach, which is presented in more details in the Electronic Supplementary Material, allows the use of analytical tools such as structural path analysis (SPA) by which the complex network system can be decomposed into individual paths (Suh and Heijungs 2007).

Beloin-Saint-Pierre et al. (2014) recently proposed a method they coined the *ESPA method* (enhanced structural path analysis), which can be used to propagate, throughout a product system, process-relative temporal information, i.e. temporal information defined at the unit process level. This propagation of process-relative temporal information is enabled by the use of convolution in the power series expansion algorithm. The typical result of the ESPA method is an inventory that expresses the timing of all emissions relative to a time 0, defined as the moment the product system's function is fulfilled, which for a specific case study could be associated to a calendar date.

The relation to generate the temporally differentiated LCI of a product system for elementary flow i is then (Beloin-Saint-Pierre et al. 2014):

$$g_i = \sum_j e_{ij} f_j + \sum_j \sum_l \left(e_{il} * b_{lj}\right) f_j + \sum_j \sum_l \sum_m \left(e_{im} * b_{ml} * b_{lj}\right) f_j + \cdots \tag{2}$$

where elements of the **B** matrix (e.g. b_{lj}, b_{ml}, b_{lj}), of the **E** matrix (e.g. e_{ij}, e_{il}, e_{im}), of the f vector (e.g. f_j) and of the g vector (e.g. g_i) are defined with process-relative temporal

distributions. Convolution (*) is a mathematical operator applied to two distributions generating a third that describes the overlap between the two when translating one of the original distributions. For example, the distribution generated by ($e_{i1} * b_{11}$) represents the translation of distribution b_{11} over distribution e_{i1}. Figure 1 shows an example of temporally differentiated LCI and convolution for a simple system.

1.3 Temporal information in LCA

Time-dependent CFs exist, and at least one method to calculate temporally differentiated LCIs has been set out. However, data is currently lacking to integrate time into LCA. The temporal information generally considered in LCA is often limited to (1) the calendar date and the duration of the studied services, as defined in the goal and scope, (2) the time frames of the life cycle stages and the temporal adequacy of the life cycle inventory (LCI) data and (3) the generic dilution, reaction and residence times of emissions used to calculate the characterization factors, along with the time horizon over which the impacts of the emissions are integrated (Phungrassami 2008). This information is insufficient to calculate time-dependent life cycle impacts.

The UNEP-SETAC Global Guidance Principles for Life Cycle Assessment Databases recommend additional temporal information in LCI databases (e.g. the moment of extraction or emission within a unit or aggregated process datasets) in order to better describe a process or an emission in LCIA and enable broader applications (UNEP 2011). Seasonal specific unit processes have begun to appear in the ecoinvent v.3 database (Weidema et al. 2013). To our knowledge, no database has included exploitable information on the duration of unit processes, the temporal profile of emissions or the timing of purchases of intermediate inputs.

1.4 Objective of this work

The effect of adding temporal information to foreground processes having already been demonstrated (Levasseur et al. 2010), the objective of this paper is to evaluate how sensitive dynamic LCA (DLCA) results are to the addition of temporal information to background processes in order to evaluate whether temporal differentiation of LCI databases would be beneficial. This sensitivity is measured by comparing the DLCA results when information on timing is considered only for the foreground system to those in which such information is considered for both the foreground and background systems. Impact assessment is limited to global warming, for which time-dependent CFs are readily available (Levasseur et al. 2010). The temporally differentiated LCIs are generated for every product in the ecoinvent v2.2 database (ecoinvent 2013) to which simplified process-relative temporal parameters were applied to selected unit processes using the ESPA method.

2 Methodology

The ecoinvent v2.2 database is used in this study as a sample database to which temporal information can be added to generate temporally differentiated LCIs for background systems and as a source of sample product systems. Replacing the final demand vector in Eq. 1 with $n \times n$ identity matrix $\mathbf{I}$ makes it possible to generate as many LCIs as there are products in

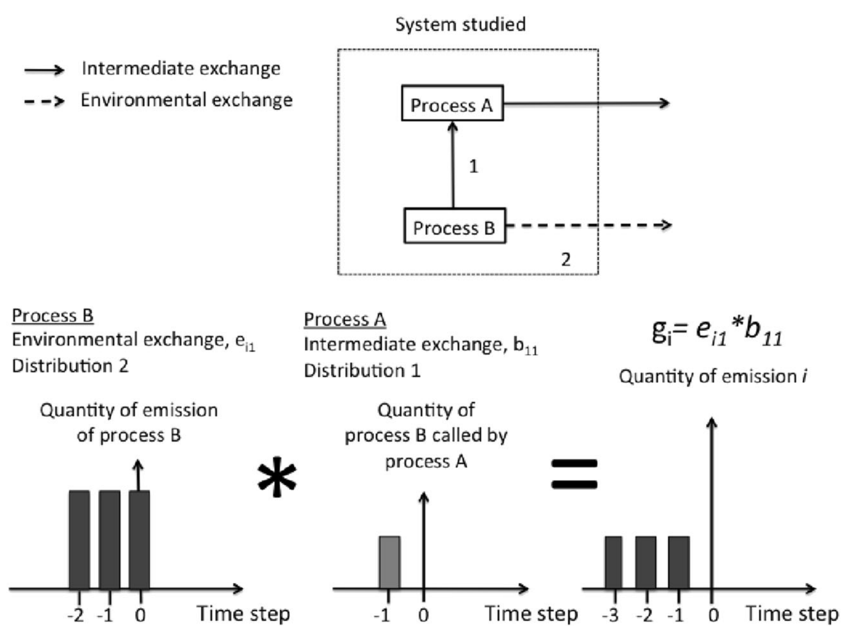


Fig. 1 Example of temporal distributions required by ESPA method

the database: the generation of 4,034 product systems that are likened, here, to LCA study cases.

In order to add the temporal information required for dynamic global warming impact assessment, unit processes to be adapted from the ecoinvent v2.2 database were identified (Section 2.1). Unit processes that are assumed to be of a certain duration were given temporal profiles consisting of phases (e.g. construction, use and demolition are the phases of infrastructure processes). These process-relative temporal phases (Section 2.2) are used to estimate the temporal distribution of intermediate and elementary flows. The data required to generate distributions for each temporal phase were collected from various sources (Section 2.3). Two sets of dynamic global warming impact scores were computed with time-dependent CFs (Levasseur et al. 2010). For each product system in the ecoinvent v2.2 database, one set only considered temporal information for the foreground system (first two tiers) and the other considered temporal information for the background system as well (13 tiers in all; Section 2.4). The two sets were then compared (Section 2.5).

2.1 Identification of relevant unit processes for adaptation

2.1.1 Selection of unit processes

Adding temporal information to the entire database would be extremely time consuming. Also, results are not likely to be significantly affected by adding temporal information to very short-lived processes. It was therefore deemed important to identify relevant unit processes for adaptation and to assume that the emissions and delivery of intermediate flows were instantaneous for all other unit processes.

Beloin-Saint-Pierre et al. (2014) acknowledge that the effort required to enter the information for all unit processes is significant even with the use of the ESPA method and therefore recommend prioritizing unit processes for which the information would be most relevant. Collet et al. (2014) suggest a selection procedure that relies on a sensitivity analysis of the impacts on the temporal variability of environmental and intermediate product flows. In their procedure, the selected flows are specific to a product system, and hence, the procedure cannot be applied to determine the unit processes to which temporal information should be added in a generic LCI database.

In past DLCA studies, the time frame of 1 year was considered relevant to global warming (Levasseur et al. 2010, 2012a, b). Therefore, unit processes for which temporal information must be added are those that collectively and cumulatively result in a 1-year difference between time 0 and the time of the emission. Using the systematic disaggregation methodology (Bourgault et al. 2012), it is possible to calculate which supply chain tier must be reached to account for a given share of cradle-to-gate impact scores.

Figure 2 shows that the 13th tier of the supply chain must be reached to guarantee that the LCI of any ecoinvent v2.2 product system will account for 99 % of the cradle-to-gate global warming impact score. In the extreme case that no temporal overlap occurs over these 13 tiers, all unit processes with a distribution time interval of at least 52 weeks/13 tiers= 4 weeks were selected for temporal adaptation. It should be noted that the minimum distribution time interval that can serve as a criterion to decide whether a unit process should be adapted will be impact category specific since impact categories will differ in the number of tiers required to account for 99 % of impacts and the time steps that are relevant.

2.1.2 Flows described with temporal distributions

The unit processes for which the temporal distributions of flows were considered non-negligible (i.e. over 4 weeks) were infrastructure processes (14 % of the database), crop and forestry (3 % of the database), stored products (4 % of the database) and disposal to landfills (2 % of the database). In the end, temporal information was added to 22 % of the database unit processes.

Transport processes, which could conceivably last for more than 4 weeks, were left out because no reliable conversion from transport units (t.km or pers.km) to time was found. Furthermore, European statistics (eurostat 2013) provide information from which average transport durations by product class could be estimated. None of the durations were over 4 weeks, and transport unit processes were therefore not considered.

Land use and land use change may be responsible for GHG emissions, depending on climatic conditions, site conditions and human activities (IPCC 2000). However, the information required to consider these issues was not available in the ecoinvent v2.2 database.

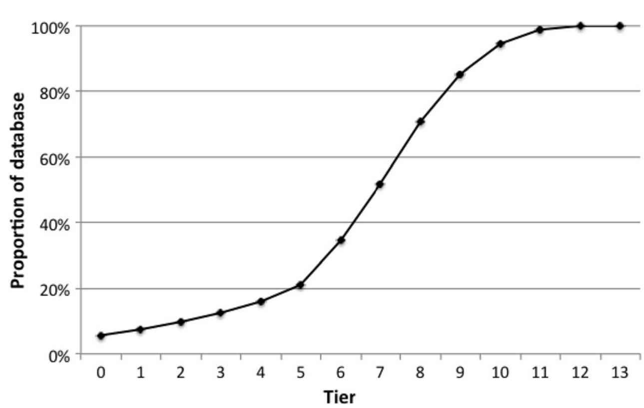


Fig. 2 Tiers at which ecoinvent v2.2 product systems reach 99 % of their respective global warming impact scores with GWPs for 100 years

2.2 Temporal parameters and temporal distributions

The selected unit processes were split into so-called phases (Table 1), whereby the duration and the position of a process-specific time 0 can be defined. Carbon uptake was assigned to the crop phase and emissions to air from landfills were assigned to the corresponding emission phase (Table 1). Specifically for the disposal to landfills unit processes, wastewater treatment infrastructures were the only intermediate flows that were temporally differentiated.

For the majority of flows, rates of use or of emissions were considered constant over time (e.g. the rate of use of intermediate flows associated with the use phase of an infrastructure process is assumed to be constant for the entire use phase (Table 1)). The temporal distributions were not assumed to be constant for carbon uptake, which was approximated by a Gaussian function defined by the rotation period of crop or forestry (Cherubini et al. 2011) or for emissions to air from landfill, which were approximated using the SWANA model for traditional landfills (Sich and Barlaz 2000).

Since it is quite difficult to know when a required product will be produced in the use phase of an infrastructure, time 0 for infrastructures was considered to occur in the middle of the use phase. The temporal position of time 0, like any other predefined parameter, can be defined by a probability density function in a probabilistic model or refined on a case-by-case basis by the LCA practitioner following a sensitivity analysis and data collection.

The process-relative parameters chosen to represent the temporal phases are described in Table 2 (see their values for each selected unit process in the Electronic Supplementary Material). Landfill unit processes for which we used the ecoinvent temporal phase definitions (short term and long term) were not described with the parameters presented in Table 2.

Table 2 Process-relative parameters added to the selected database unit process to determine temporal distributions

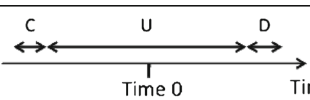
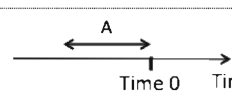
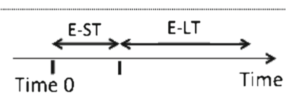
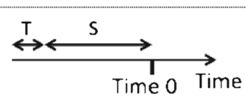
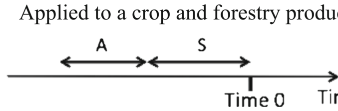
Parameters	Description
Replacement material proportion	Ratio defining the proportion of intermediate product flows (materials/fuels/electricity) and elementary flows occurring during the construction and use phases, and the ratio of waste occurring during the use and demolition phases
Rotation time (h)	Duration of the crop phase and the associated carbon uptake function
Storage time (h)	Duration of the storage phase
Construction time (h)	Duration of the construction phase
Infrastructure occupation (h)	Duration of the infrastructure use phase
Demolition time (h)	Duration of the demolition phase

2.3 Data collection and integration

Most of the data were collected from ecoinvent v2.2 literature reference documents. When data was not available, assumptions or proxies were used. More information on the assumptions made during data collection is available in the Electronic Supplementary Material.

The temporal parameters were used to define the elements of technological matrix **A** and intervention matrix **E**. Each unit process in the ecoinvent v2.2 database was described with

Table 1 Phases according to unit process category

Unit process	*Phases*	*Legend*
Infrastructure		C, Construction phase U, Use phase D, Demolition phase
Crop and forestry		A, Crop
Landfills		E-ST, Emissions short-term (in the first 100 years) E-LT, Emissions long-term (over 100 years)
Product being stored	 Applied to a crop and forestry product: 	A, Crop S, Storage T, Transformation of product

a list of values representing the amount of intermediate or elementary flow for each time step (in this case, 4 weeks) and a time zero position, which indicates the time step that corresponds to time 0. For example, the environmental exchange of process B in Fig. 1 could be described in traditional LCA with an emission of 3 kg, which, in DLCA, would correspond to the list of values [1; 1; 1]. Time 0 lines up in this case with the third element of the list. For flows that were considered instantaneous, only the time 0, relative to the time of the instantaneous flow, needed to be defined.

As a more realistic example, consider a wood product LCA which includes a unit process describing the growth of a tree. Suppose that the product system t=0 is the time the wood product is used, that there is a 6-month period between the time the tree is harvested and the time the wood product is used, and that the rotation age of the forest where the tree was harvested is 80 years. At the unit process level, the carbon dioxide uptake temporal profile associated with tree growth would be represented by a list of values that represent the quantity taken up for every 4-week period in the 80 years of the tree growth, with the unit process t=0 being the date the tree is harvested. When building the life cycle inventory using Eq. 2, the timing of carbon dioxide uptake is described by this unit process level temporal profile translated by the 6 months that separate the tree harvest and the product system t=0. Each carbon dioxide uptake entry is characterized using time-dependent CFs that correspond to the time between the specific moment of carbon uptake and the time horizon of the study (e.g. 100 years after the use of the wood product, i.e. t= 100 years).

2.4 Computing DLCA

The following steps were applied to implement the DLCA method:

1. For each commodity in the ecoinvent v2.2 database, a "traditional" (i.e. non temporally differentiated) LCI and a corresponding global warming impact score were generated using the matrix inversion approach. The global warming impact was calculated using traditional characterization factors based on GWP100 (Forster et al. 2007).
2. For each commodity in the database
   (a) The inventory with temporally differentiated foreground and background processes was generated (tree representation in Fig. 3a). For each selected intermediate flow (e.g. b_{11}, the first intermediate flow of the unit process 1 of tier 0), the elementary flows of the corresponding unit process (e.g. e_{i1}, for the flow i of the unit

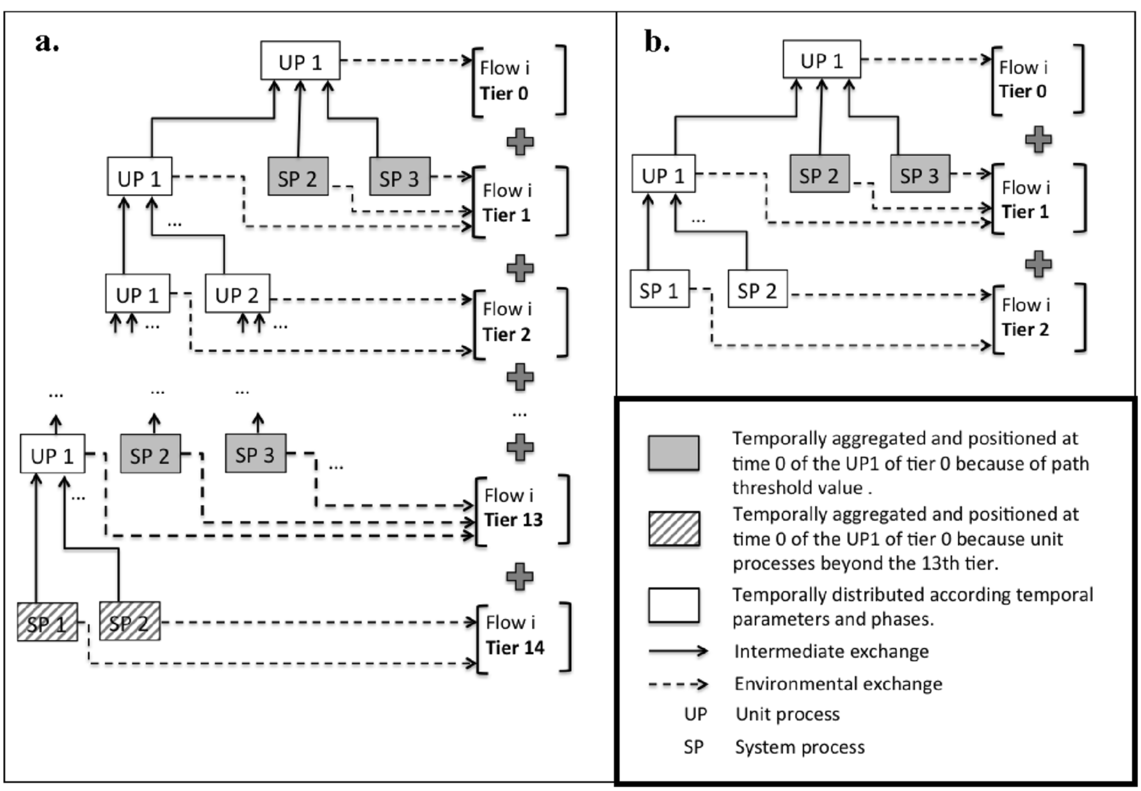


Fig. 3 Example of elementary flows, system (i.e. aggregated) processes (SP) and unit processes (UP) considered when generating the temporally differentiated LCI of a product system with **a** background processes temporally differentiated until the 13th tier or with **b** only temporally differentiated foreground processes

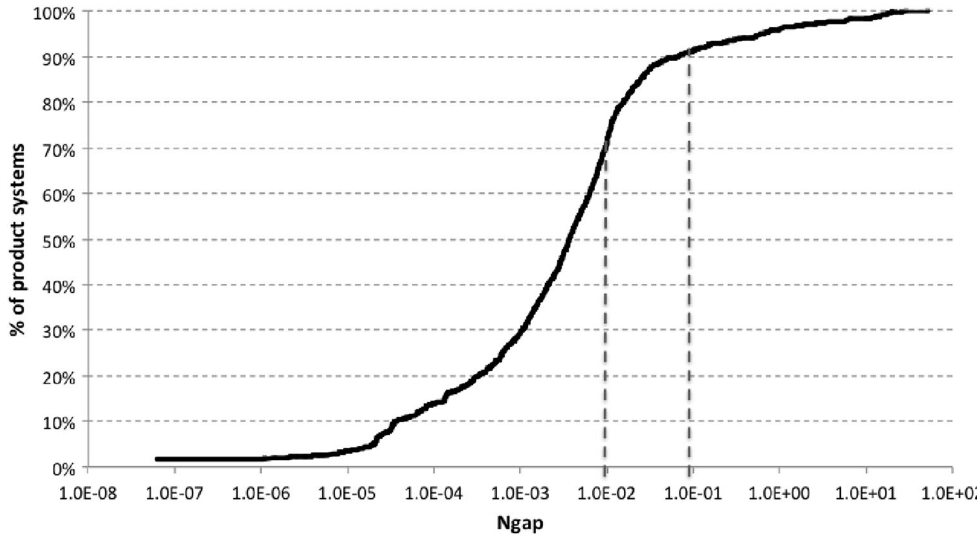


Fig. 4 Cumulative proportion of database product systems based on the normalized gap of impacts (Ngap)

process 1 of tier 1) were scaled according to Eq. (2) (e.g. $(e_{i1} * b_{11})$ in Fig. 3a). The time zero position of these scaled elementary flows was also updated. The addition of the scaled elementary flows generated the temporally differentiated inventory. Unit processes beyond the 13th tier, which, as shown above, can collectively contribute to up to 1 % of the global warming scores, were included in the inventory and considered at time 0 of the UP1 of tier 0 (i.e. all emissions from the path were addressed as in traditional LCA). Paths contributing less than a threshold value of 2×10^{-4} % were also considered at time 0 of the UP1 of tier 0. The threshold value is based on a compromise between the completeness of the temporal information and computation time (see Electronic Supplementary Material for more details). The global warming impact scores were calculated using time-dependent characterization factors for a fixed time horizon of 100 years (i.e. the impacts of emissions occurring at −150 years according the product system time 0 were integrated over 250 years) (Levasseur et al. 2010).

(b) The inventory with only temporally differentiated foreground processes was generated (tree representation at Fig. 3b). To generate this temporally differentiated inventory, elementary flows were addressed with the same approach described in 2a, but only until tier 1. The elementary flows of the next tiers were considered instantaneous, occurring at the time specified by unit processes in tier 1. The global warming impact scores were calculated using time-dependent characterization factors for a fixed time horizon of 100 years (Levasseur et al. 2010).

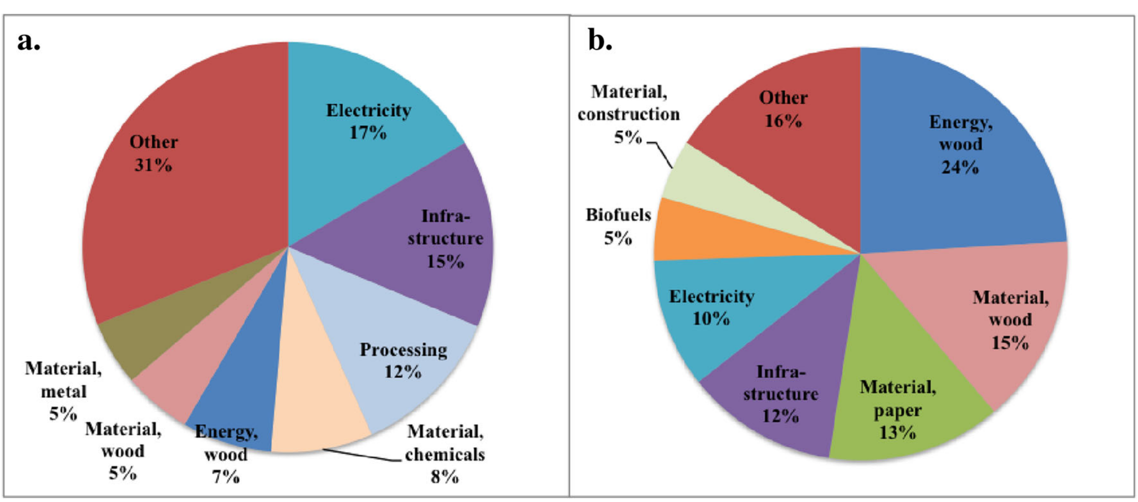
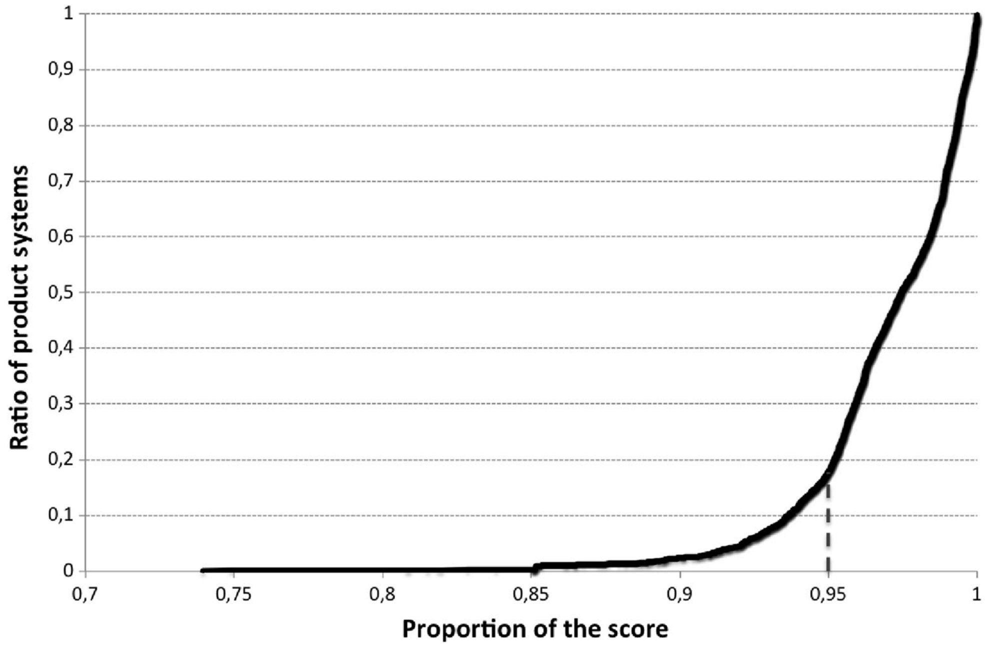
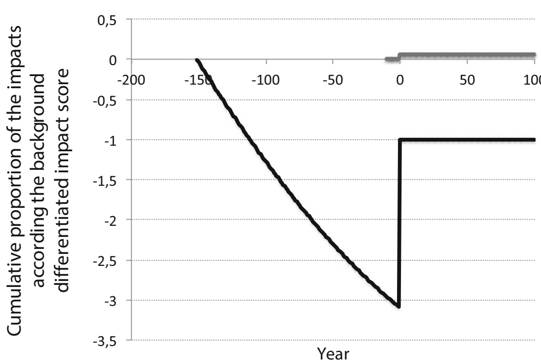


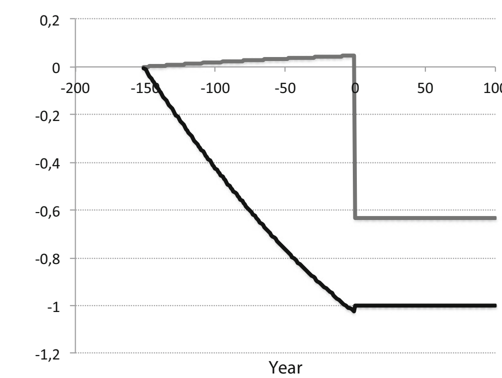
Fig. 5 Categorization of product systems with a normalized gap (Ngap) **a** over 1 % (29.1 % of database product systems) and **b** over 10 % (8.6 % of database product systems)

Fig. 6 Proportion of database product systems based on the proportion of global warming score with background unit processes temporally differentiated calculated with time-dependent CFs

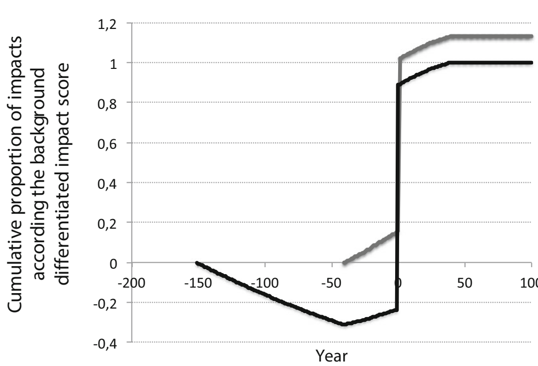




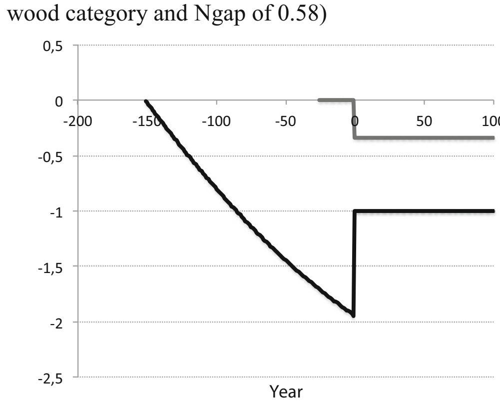
a. Wood chips, burned in cogen 6400kWth/CH U (energy wood category and Ngap of 19.03)



b. Wood wool, u=20%, at plant/RER U (Material, wood category and Ngap of 0.58)



c. Cement plant/CH/I U (infrastructure category and Ngap of 0.12)



d. Paper, woodfree, coated, at integrated mill/RER U (material, paper category and Ngap of 1.96)

—foreground **—background**

Fig. 7 Profiles of dynamic impacts. **a** Wood chips, burned in cogen 6,400 kWth/CH U (energy wood category and Ngap of 19.03). **b** Wood wool, u= 20 %, at plant/RER U (material, wood category and Ngap of 0.58). **c** Cement plant/CH/I U (infrastructure category and Ngap of 0.12). **d** Paper, woodfree, coated, at integrated mill/RER U (material, paper category and Ngap of 1.96)

2.5 Systematic comparisons

Dynamic global warming impacts for each of the product systems in the ecoinvent v.2.2 database were compared in order to determine whether the temporal differentiation of background processes significantly affects the results. The comparison is carried out with the normalized gap of impacts (Ngap) of each product system:

$$\text{Ngap} = \text{abs}\left[\frac{(\text{Impacts with temp. diff. background} - \text{Impacts with temp. diff. foreground})}{\text{Impacts with temp. diff. foreground}}\right] \quad (3)$$

The most affected process categories reveal the type of study cases that would benefit from this type of information in LCI databases.

3 Results and discussion

For 29.1 % of the database product systems, the normalized gap of the global warming impact is over 1 %, as shown in Fig. 4. Considering temporal information in the background unit processes decreases the global warming impact scores for 95 % of the product systems due to the high sensitivity to carbon uptake temporal differentiation. Not including a temporal differentiation of background unit processes would then lead, in most cases, to an overestimation of impacts on global warming. According to the rule of thumb of 10 % defining a significant difference between global warming scores suggested by Humbert et al. (2009), the temporal differentiation of background processes significantly affects the LCA scores

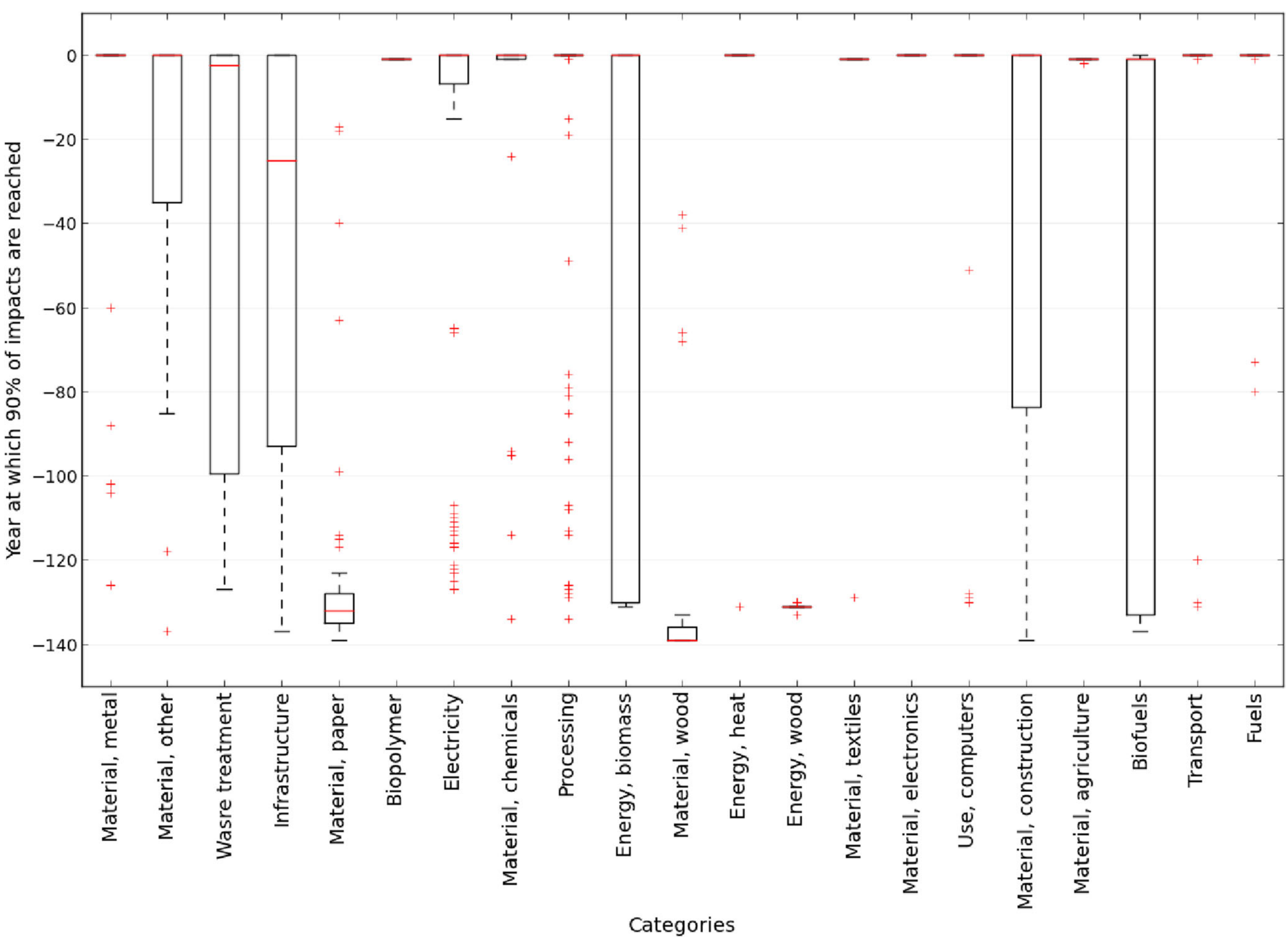


Fig. 8 Year relative to the product system time 0 at which 90 % of a product system impact score are reached for product systems with a normalized gap (Ngap) over 1 %

for 8.6 % of the database product systems. For all of these product systems, the global warming impact scores had decreased following the consideration of temporal differentiation of background unit processes.

The product systems that are most sensitive to the temporal differentiation of background unit processes are from the wood sector (e.g. wood products, paper and board material) and those using wood products (e.g. energy from wood). The infrastructure, electricity, biofuels, processing and chemical categories were also sensitive to the temporal differentiation of the background (see Fig. 5). Again, this is due to the high influence of carbon uptake on the climate change category scores.

The results are for the arbitrary definition of what constitutes typical foreground processes chosen in this paper, i.e. first two tiers following the process supplying the reference flow. Alternate definitions, such as e.g. more numerous processes along a specific supply chain, could lead to very different results and were not explored for this paper.

The choice of the threshold value of 2×10^{-4} % for temporal differentiation impacted the proportion of global warming score calculated with time-dependent CFs. The proportion of the score calculated with time-dependent CFs was higher than 95 % for 96 % of the database product systems (see Fig. 6).

Impact profiles of product systems are presented as examples in Fig. 7. Profiles with and without background differentiation are more different in the cases of wood chip, wood wool, cement plant and paper processes because of a high amount of wood products in supply chain backgrounds. The temporal differentiation of carbon uptake during wood growth is responsible of the profile between −150 and 0 year observed on Fig. 7a–d. The tree growth duration for hardwood and softwood unit processes was 150 years (see Electronic Supplementary Material for the unit process temporal data) so that if wood was used at time 0 of the product system, the carbon uptake profile extends from −150 to 0 year. As stated in Section 2.4, it would mean that carbon uptake occurring at −10 years, i.e. 10 years before its use, would be assessed with a CF that represents radiative forcing over a period of 110 years, representing 10 years to t=0+100 years to the fixed time horizon of 100 years starting from t=0.

The increase in impact is observed after time 0 for infrastructures (see Fig. 7c) because the infrastructures' time 0 were assumed at the middle of its use phase. Impacts following time 0 in these cases refer to the impacts occurring during the second half of the use phase and the end-of-life phase.

In Fig. 8, the year relative to the product system time 0 at which 90 % of impacts are reached is shown for each product system with an Ngap over 1 %. Ninety percent of the impact is calculated from +200 years to −200 years. Considering the case of "energy" and "wood", the results should be interpreted as 90 % of the impacts occur between −130 years and + 200 years. Then, less than 10 % of the impacts occur before −130 years, which is consistent with the profile of Fig. 7e for instance. This year is far in the negative (over 100 years) in some cases due to the high crop rotation of softwood (150 years).

4 Conclusions

Considering the sometimes significant difference between dynamic results with and without background process differentiation, adding temporal information to unit processes in LCI databases would enable a more accurate global warming impact assessment, at least in some cases. According to the results presented above, the enhancement would benefit LCAs in which products of biomass are present in substantial amounts.

Collecting sufficient temporal information to differentiate background unit processes is not an easy task and therefore cannot be expected to be carried out for specific LCA studies. We recommend centralizing the collection and inclusion of this type of data by making it the responsibility of database providers. The integration of process-relative temporal parameters into LCI databases would limit the time and effort required to inform about the moment when intermediate and elementary flows occur. Since values of Ngap were mostly sensitive to rotation time and infrastructure parameters, they should be prioritized for further work and for integration in databases. However, the time step used in this study was relevant for the global warming impact category and may therefore need to be refined to cater to other impact categories.

The temporal information discussed in this paper for LCI databases would also facilitate the implementation of DLCA by practitioners. This increase in the level of operationalization could, hopefully, lead the method's broader use by LCA analysts.

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